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A DATA DRIVEN APPROACH OF MODELLING AND PARAMETER ESTIMATION OF BOILER DRUM SUBSYSTEM DYNAMICS

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ABSTRACT

A nonlinear dynamic model of the boiler drum level system is estimated from plant data. The identified models describe the dynamic behaviour of the subsystem under a given operating condition. Both linear and nonlinear models are estimated and compared for the validation of the model. The model is simulated and results are presented. The effect of load variation on the drum level changes from time to time with respect to power demand posing a challenge on drum level control. The presented model provides a dynamic model derived from real plant data which can be effectively used for the design of model based control schemes.

KEYWORDS: Boiler Drum Level Control, Dynamic Modelling, System Identification, Parametric Modelling

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Original Article

INTRODUCTION

Steam boilers are the devices employed to generate steam for power generation. The generation of the steam should be controlled in accordance with the power generation demand. The amount of feed water supplied to the boiler drum must be increased for an increased demand of power. Similarly for a reduced power demand the inflow of the feed water must be decreased. Despite the power demand fluctuations and varying feed water supply, monitoring and control of drum level is demanded to maintain the quality of the steam generated. Excess drum water level than the required will result into wet steam causing damage to the turbine blades. On the other hand, lack of sufficient water in the drum can cause overheating of the boiler tubes. Hence, in order to improve the efficiency of the boiler, a proper synchronization of power demand signal, steam generation, drum level and feed water is important.

EFFECTS OF SHRINK AND SWELL ON DRUM LEVEL

The shrink and swell are the phenomenon observed in stem drum due to the formation and collapsing of water bubbles as shown in figure 1.

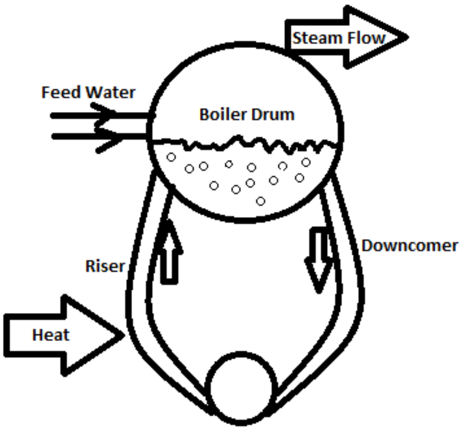

Figure 1: Drum Boiler system

The increased power demand causes more steam generation and consequently more number of water bubbles is formed. This causes an apparent rise of drum water level and this phenomenon is called “swell” effect. When the demand of the power decreases the steam bubbles collapses due to the increased pressure in the drum and decreases the drum water level. This phenomenon is called “shrink” effect shown in figure 2. The inverse characteristics due to the shrink-swell effect must be considered for obtaining optimal drum level control.

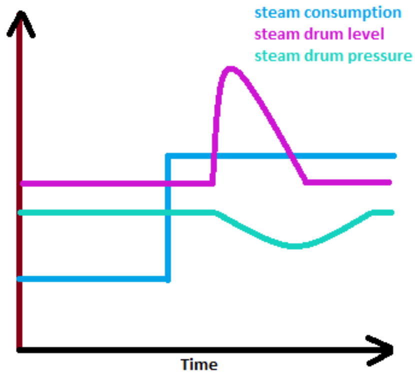

Figure 2: Shrink-Swell Effect on Drum Level

SYSTEM IDENTIFICATION

The behaviour of the drum boiler unit is determined by a set of processes. Each process is determined by its elements and variables which may not be clearly defined by mere underlying principles. The modelling aims at bringing out these essential aspects that form the dynamics of the process. Identifying unknown system based on its cause (input) and effect (output) data is referred as system identification. System identification is the process of identifying the dynamic models of physical systems based on experimental or real time data. It is an iterative process as given in figure3 and consists of following steps.

- The general identification procedure starts with understanding the basic underlying principles of a system and acquiring prior knowledge.
- Designing an appropriate experiment that has a potential to reveal the most significant dynamics of the system.
- Collecting suitable portion of experimental data which can reflect the appropriate relation of cause and effect.

- Select suitable model structure.
- Select appropriate criterion for analysing the model fit.
- Estimate the model.

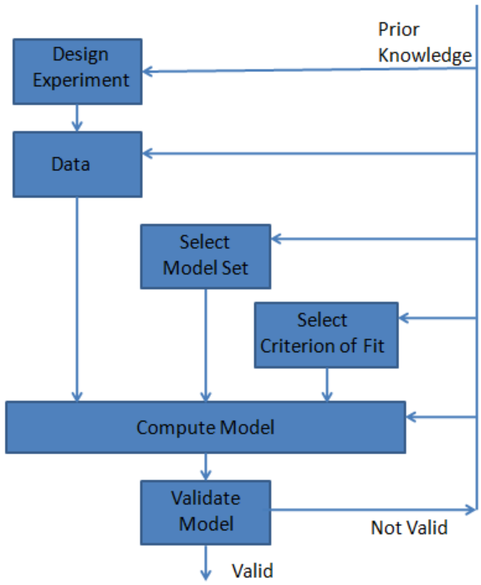

Figure 3: Process of System Identification

Validate the model if the estimates are satisfactory if not repeat the procedure from step 4. Maintaining drum level is required for stable operation of the boiler. The typical range of level fluctuation in the drum is observed as few cm [1]. The optimal control of drum level can be achieved by considering all the nonlinearities and inverse properties. Different improved and modified feedback [2] control theories are emerging. Use of model based control is gaining importance in improving the plant efficiency [3].

Modelling techniques are broadly classified as white box and black box models. White box models are simple models based on the understanding of the basic underlying principles such as mass balance, energy balance equations and other physical and chemical laws. Black box models are completely data driven and does not require prior knowledge of the system. The data driven models describe the dependency of output on input. The other dynamic characteristics of the physical system such as delay, response rate, time constant etc are not interpreted in direct form but through analysis of results [4]. The gray box models are used when only partial information of the physical system is at hand and the complete model must be estimated based on both partial prior knowledge and experimental data. The main aim of drum model identification is to understand the dynamics identify the interaction of other variables and design of control [5].

The first step in designing the experiment is selecting appropriate sampling frequency to generate quality time series raw data. Any outliers or lost data should be treated first before using this raw data for identification. A simple time series can be represented as sequence of output y(kT) and input x(kT). Where T is sampling interval and k is sampling instance defined at k=(0, 1, 2,..., N), where N is number of samples. The commonly used concepts for time domain analysis are auto regression and autocorrelation. The power density spectrum plays major role in frequency domain analysis. Time series data can also be used with wavelet transform techniques. The data driven models can be of linear type such as linear time invariant (LTI), transfer function (TF) etc. The nonlinear models are estimated by using orthogonal

series such as Volterra series, nonlinear ARX and Hammerstein – Wiener and dynamic matrix control models [6] etc.

PARAMETRIC MODELLING RESULTS AND CONCLUSIONS

Parametric models provide simple models containing parameters with in a predefined structure. The standard black box models can estimated with different structures viz. ARX, ARMAX, OE, BJ and FIR. Most of the industrial processes can be estimated with simple ARX model such as given in figure 4.

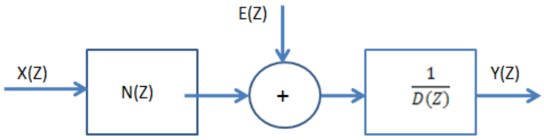

Figure 4: ARX Model Structure

The output of the ARX type system can be expressed as

$$\boldsymbol{Y(z) = G(z)X(z) + H(z)E(z) = \frac{N(z)}{D(z)}X(z) + \frac{A(z)}{B(z)}E(z)} \quad (1)$$

Where G(z) is the transfer function of the system and H(z) is transfer function of noise expressed in terms of polynomials. The estimation problem of ARX model is expressed as linear regression type, which is easier to estimate. The order of the polynomial should be selected high inorder to overcome the effect of signal to noise ration. The estimated models can be validated using different types of criteria viz. maximum likelihood (ML), least squares (LS), instrumental variable (IV) methods.

The dynamic properties of the drum, down comer, riser, turbine and generator units can be identified and used in the design of control system [7]. The real time data of feedwater flow rate (in GPM) and actual drum level (in cm) collected from boiler unit 4 is shown in table 1 is considered for estimating the different models.

Table 1: Sample of Real Time Data

Date/Time	4 Drum Lvl Actual. out. sample	4 Total MS Flow. out. sample	4 Total Fd Wtr Fw. out. sample	4 Drum Lvl SP. out. sample	43 E Error. out. sample	4 BFP Scoop Mstr. out. sample	4 load actual MV3. out. sample
06:10.0	-144.297	650.1588	642.5738	-144	0.3129	75.1224	209.4149
06:20.0	-148.058	650.3763	642.6508	-144	0.518	75.3293	209.5751
06:30.0	-146.93	650.5049	643.0286	-144	0.5181	75.4145	209.8384
06:40.0	-146.348	650.7719	642.6877	-144	0.4708	75.3899	209.6667
06:50.0	-148.776	650.8213	637.3232	-144	0.8425	75.6378	209.621
07:00.0	-148.776	650.7817	648.6959	-144	0.4106	75.5146	209.5523
07:10.0	-147.458	651.0586	647.2201	-144	0.3795	75.4199	209.2547
07:20.0	-148.518	651.4047	645.6731	-144	0.4999	75.4481	209.4607
07:30.0	-148.535	651.3652	646.5627	-144	0.4713	75.5461	209.289
07:40.0	-149.492	651.3652	646.0391	-144	0.5132	75.5913	209.8956
07:50.0	-148.791	651.4344	643.5823	-144	0.5859	75.6836	209.4149
08:00.0	-150.569	651.5432	642.4664	-144	0.8176	75.8789	209.4264
08:10.0	-149.988	651.6124	650.9464	-144	0.4002	75.6546	209.5981
08:20.0	-149.133	651.6322	649.1604	-144	0.3959	75.6194	209.3233
08:30.0	-155.515	651.4542	651.1898	-144	0.693	75.8026	209.2547
08:40.0	-151.088	651.4641	650.4918	-144	0.4614	75.8036	209.5179
08:50.0	-147.584	651.4344	651.2723	-144	0.1994	75.6566	209.3577

The structure of ARX model (3,1,3) is found suitable using an auto structure function in MATLAB. The selected structure given by Akaike's information criteria (AIC) indicates that drum level model is estimated by using four (3+1) regressors, three related to output drum level eg. y(t-1), y(t-2) and y(t-3), one related to input feedwater flow rate u(t-1). Different linear models are estimated and are compared. The discrete ARX model is given by equation 2.

$$A(z)y(t) = B(z)u(t) + e(t) \tag{2}$$

Where the polynomial functions A and B are given by equations 3- 4.

$$A(z) = 1 - 0.7909z^{-1} + 0.2619z^{-2} - 0.4699z^{-3} \tag{3}$$

$$B(z) = -0.0001599z^{-3} \tag{4}$$

The estimated model is fit to estimation data by 71.39%. The prediction error (FPE) and mean square error (MSE) are identified as 4.155 and 3.928. The state space model represented by equations 5-6.

$$\frac{dx}{dt} = Ax(t) + Bu(t) + Ku(t) \tag{5}$$

$$y(t) = Cx(t) + Du(t) + e(t) \tag{6}$$

The identified state matrices are given by A, B, C, D and K.

$$A = \begin{matrix} -5.378 & -20.14 \\ 27.1 & -70-71 \end{matrix} \tag{7}$$

$$B = \begin{matrix} -0.9072 \\ -2.859 \end{matrix} \tag{8}$$

$$C = 70.35 \quad -6.467 \tag{9}$$

$$D = 0\,;\; K = \begin{matrix} 0.4026 \\ -1.517 \end{matrix} \tag{10}$$

CONCLUSIONS

In this paper the boiler drum model for level control is estimated using closed loop parametric system identification techniques. Both ARX and NARX models are estimated using historic data of boiler unit 4. It is identified that the estimated model is fit to estimation data by 67.34%, the FPE is 5.461 and MSE is 5.122. Estimated linear models are validated against estimation data and the results are compared. The simulated response of linear ARX model is presented in figure6.

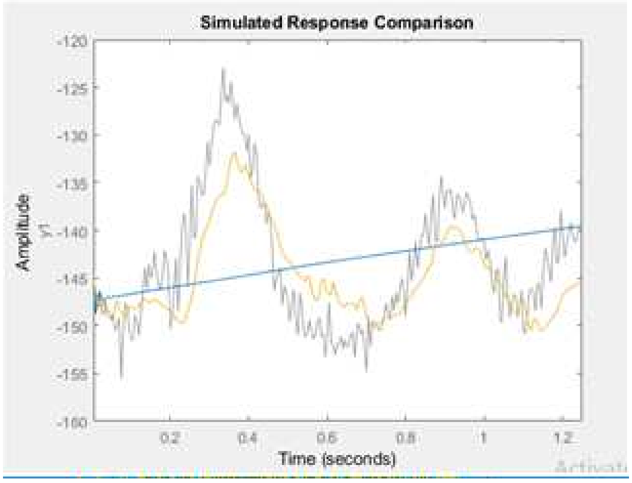

Figure 6: Simulation Response of Linear ARX Model

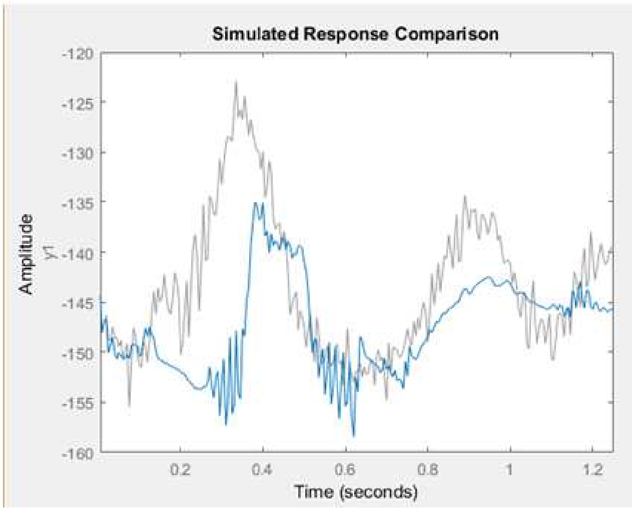

Figure 7: Simulation Response of Nonlinear ARX Model

More improved fit is achieved with nonlinear ARX model as presented in figure7. The FPE and MSE are also minimized to 3.686 and 2.124 giving a fit of 78.96% on estimation data. Simulation results shows that nonlinear dynamics of drum level control loop are better described by NARX model. Boiler drum can also be modeled using Hammerstein-Wiener model. The modeling and study of individual sub systems of boiler such as drum, down comer, riser, feed water control valve, throttle valve etc helps in designing more robust control structures.

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